Adaptive Object Classification using complex SAR Signatures

Firooz Sadjadi
Lockheed Martin Corporation
Eagan, Minnesota
firooz.sadjadi@ieee.org

Abstract

This paper addresses the problem associated with the classification of signatures of objects obtained by coherent sensors whereby the signatures are complex valued. Individual phase and amplitude component of a signature are combined optimally and the resulting fused signature is used in a sparsity-based learning classifier. The results of application of this approach are then compared with the corresponding results using only the amplitudes of the signatures. To test the concept public-domain radar signatures of several land vehicles obtained at different aspect angles are used. The performance improvement, based on confusion matrices, is shown to be significant when both phase and amplitudes are used

1. Introduction

One of the important steps in remote sensing is the classification of signals, whereby signatures received by a sensor is labeled. In the case of coherent sensors, the signature is complex valued and can be represented by its joint phase and amplitude components. However, classification methods used for the signatures obtained by these sensors have rarely made use of their complex nature and relied only on their amplitudes.[1, 2, 4, 3, 5]. However a number of attempts were also made to explore the problem of image classification when the sensor outputs are characterized by complex valued random variables. In one such effort [6] for classification Raleigh quotient that is a bound on the Bayesian total probability of error was derived for complex signatures which showed significant improvement over the amplitude-only signatures using real SAR imagery. In the present work we continue this effort by using a sparsity-based learning classifier and show similar improvements over amplitude -only classification results. In this work we use a set of publicly available complex SAR images of land-vehicles that were collected by an X-band radar. The object signatures were available at varying aspect angles. For the case of complex signatures the phase and amplitude components were optimally combined to generate a fused signature and the result of its classification was compared with those of the amplitude-only signatures using confusion matrices. In both cases, from each signature a set of invariant attributes was extracted and used as input to the classifier for training and testing. It will be shown that the joint phase and amplitude significantly improves the classification resultants.

2. Sparsity-based approach

This is a learning classifier where we search for a representation that approximates elements of a target class with as few training samples as possible. Sparse representation attempts at modeling of data vectors as a linear combination of a few elements from a set called dictionary. Methods to adaptively determine the elements of this set (basis functions) are also called dictionary methods[7, 8, 9]. If the number of samples is smaller than the dimension of the training signal we would be dealing with an overdetermined case and a unique solution should exist. However when the number of samples is larger than the signal dimension, we would be encountering an under-determined and additional constraints would be required to obtain a solution.

2.0.1 Sparse representation-based classifier

In this method the following steps are taken:
1: Input: a matrix of training samples $A = [A_1, A_2, ..., A_k] \in \mathbb{R}^{m\times n}$ for k classes, a test sample $y \in \mathbb{R}^m$,
(and an optional error tolerance $\epsilon > 0$).
2: Normalize the columns of A to have unit$L2$-norm.
3: Solve the $L1$-minimization problem:

$$x = arg\, min_x ||x||_1 \text{ subject to } ||y - Ax||_2 < \epsilon. \tag{1}$$

4: Compute the residuals $r_i(y) = ||y - A\delta_i(x_i)||_2$ for $i = 1, 2, ..., k$.
5: Output: $identity(y) = arg\, min_i\, r_i(y)$.

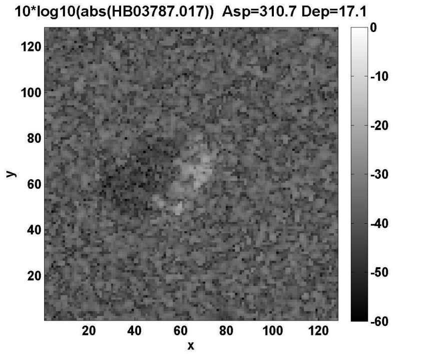

Figure 1. A Magnitude SAR image of a T72 Tank

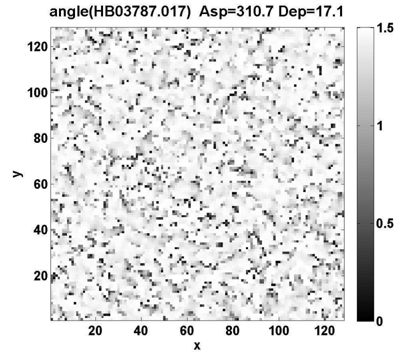

Figure 2. A phase SAR image of a T72 Tank

In the above for each class i, let $\delta_i : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be the function that selects the coefficients associated with the ith class. For $x \in \mathbb{R}^n, \delta_i \in \mathbb{R}^n$ is a new vector whose only nonzero entries are the entries in x that are associated with class i.

3. Experimental results for classification using dictionary learning method

We used the amplitude and phase training samples of 3 distinct classes of targets from MSTAR data set to build a dictionary. For testing we used testing samples from each class. The result for both complex and amplitude-only cases will be shown in the form of Confusion Matrices.

3.0.2 MSTAR Data sets

For this study SAR signatures three different land vehicles were used that include both military and non-military vehicles and were consisted of T72 tank, BTR70 transport vehicle and D7 Bulldozer (see the following Figs). These signatures had been collected as part of the Moving and Stationary Automated Target Recognition (MSATR) program in 1990's and were distributed by the Air Force Research Laboratory under Public Domain data sets. The sensor used was an X-band radar, horizontally transmitted and received (HH).

The following Figs show both magnitude and phase SAR images of a T-72 tank.

3.1. Fusing phase and amplitude parts of the signatures

The magnitudes and phase of the signatures were combined[10] in one signature by selecting at each pixel the optimum fused value based on a set of performance metrics and image fusion algorithms. In the following the results for using. For illustration purposes, using T72 signatures, the metric results for three fusion metrics, Fechner Weber (FW), entropy, and Fisher distance using 12 different fusion algorithms are shown in Figs 3, 7, 6, and 8. The fusion

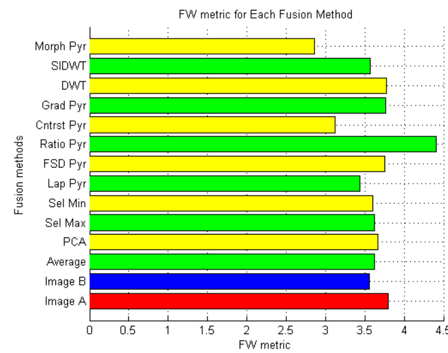

Figure 3. FW metric for various fusion algorithm used on T72 tank magnitude and phase signatures

algorithms were: Maximum likelihood estimate/Total Probability Density Function (TPE), Principal Component Analysis (PCA), Laplacian Pyramid, Filter-Subtract-Decimate Hierarchical Pyramid (FSD), Ratio Pyramid, Gradient Pyramid, Discrete Wavelet Transform (DWT), Shift Invariant Discrete Wavelet Transform (SIDWT), Contrast Pyramid, Morphological Pyramid, and a Bio-inspired methosd The results of applying four of the fusion algorithms are shown in Figs 4, 5, 6, and 9. These Figs show fused magnitude and phase images using Pyramid Ratio, Contrast Pyramid, Principal Component Analysis(PCA), and Morphological Filter fusion algorithms. We performed this operation for each target class.

3.2. Classification using magnitude-only SAR signatures

In this experiment we used only magnitude values of the SAR signalers from BTR70 Transport, T72 tank and D7 bulldozer vehicles. First algebraic invariant features for each signature was obtained and used as a training sample in the classifier. This was done to reduce the dimensionality of the signature and also to exploit geometrical invariance of target signatures.

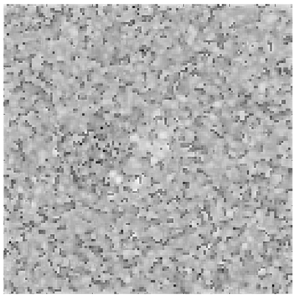

Figure 4. Fused magnitude and phase for T72 tank using Pyramid Ratio algorithm

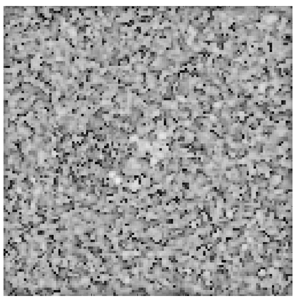

Figure 5. Fused magnitude and phase for T72 tank using Contrast Pyramid algorithm

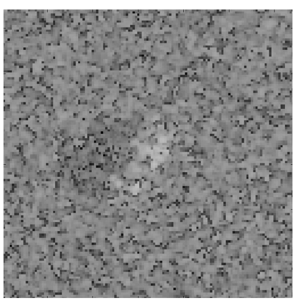

Figure 6. Fused magnitude and phase for T72 tank using PCA algorithm

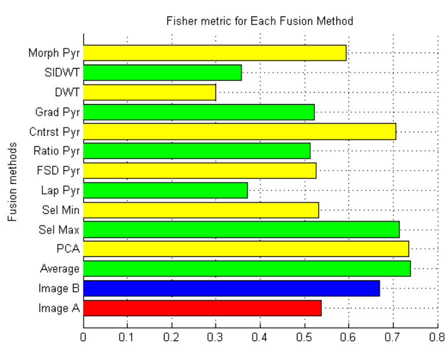

Figure 7. Fisher metric for various fusion algorithm used on T72 tank magnitude and phase signatures

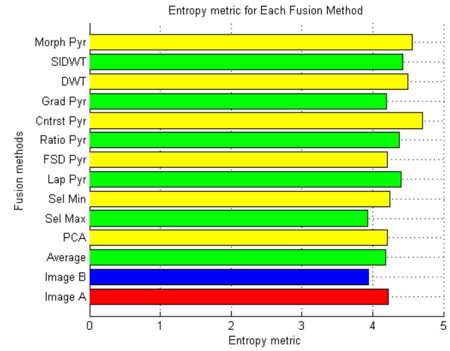

Figure 8. Entropy metric for various fusion algorithm used on T72 tank magnitude and phase signatures

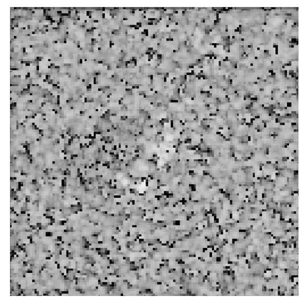

Figure 9. Fused magnitude and phase for T72 tank using Morphological algorithm

3.2.1 2D algebraic invariants

These features are algebraic expressions that remain unchanged under 2d rotation, scale and position in the field of view [12, 11]. Consider a homogeneous nth order polynomial of m variables. In the parlance of invariant algebra this polynomial is referred to as an m-ary quantic of order n (or m-ary n-ic). The goal pursued under this theory is the derivation of those algebraic expressions of the coefficients of this quantic that remain invariant when the m variables undergo a linear transformation. The coefficients of the transformation act as a multiplying factor. When this factor is eliminated the invariants are referred to as absolute invariants. Now any 2D real-valued array can be represented as a For the case of Binary quantic the following invariants can be derived: an unnormalized probability density function that itself can be represented in terms of an infinite number of its statistical moments through the moment generating function which is a binary polynomial (binary quantic). Thus a set of absolute invariants can be obtained in terms of these moments. Seven of these invariant expressions are tabulate below.

$$
\begin{aligned}
\phi_1 &= \eta_{20} + \eta_{02} \\
\phi_2 &= (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \\
\phi_3 &= (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} + \eta 03)^2 \\
\phi_4 &= (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \\
\phi_5 &= (\eta_{30} - 3\eta_{12})(\eta_{12} \\
&\quad + \eta_{30})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2)] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] \\
\phi_6 &= (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \\
\phi_7 &= (3\eta_{12} - \eta_{30})(\eta_{30} + \eta_{12})[(\eta_{30} \\
&\quad + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] \\
&\quad + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]
\end{aligned} \tag{2}
$$

in the above equation ηs are related to the $p + q$ centralized statistical moments of a 2D array μ_{pq} by the following normalization equation:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{00}^{\frac{(p+q)}{2}+1}} \tag{3}$$

3.3. Classification using combined phase and magnitude SAR signatures

In these experiments combined magnitude and phase SAR signatures of T72, D7 and BTR70 were used in both training and classification. The combination or fusion was done as described earlier in this report. Specifically the results of using Contrast Pyramid fusion algorithm was used for combining phase and magnitude of T72 SAR signatures and Ratio Pyramid algorithm was used for combining magnitudes and phases for both BTR70 and D7 SAR signatures. Once again as was the case for the magnitude-only classification process we used the invariant attributes to build a dictionary from the three target signatures originating from 3 distinct target and non-target classes. For testing we used 10000 training samples from each class and added different samples of Gaussian random noise to them. The result using $mean = 0.1$ and $\sigma = 0.1$ are shown in the form of a Confusion Matrix in Fig 10. The resulting Confusion Matrix when the $mean = 0.5$ but $\sigma = 0.1$ is shown in Fig 11. The resulting Confusion Matrix when the $mean = 0.5$ but $\sigma = 0.5$ is shown in Fig 12. The resulting Confusion Matrix when the $mean = 0.75$ but $\sigma = 0.5$ is shown in Fig 13. As can be seen increasing the value of $mean$ σ led to degradation in the classification performance. In particular some small performance degradation can be seen for D7 signature.

The most significant observation, however is that using both magnitude and phase has led to noticeable improvement in the classification performance.

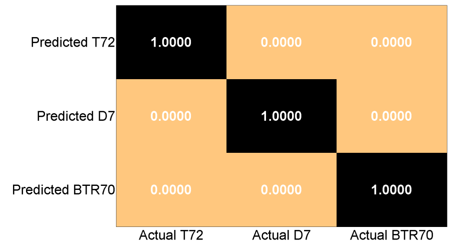

Figure 10. Confusion matrix for 3 target classes using mean=0.1 and variance=0.1. Combined magnitude and phase is used

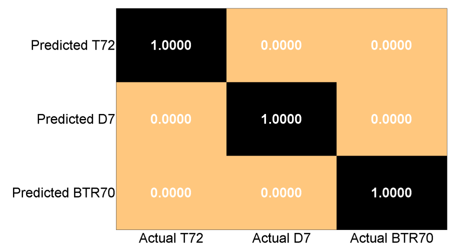

Figure 11. Confusion matrix for 3 target classes using mean=0.5 and variance=0.1. Combined magnitude and phase is used

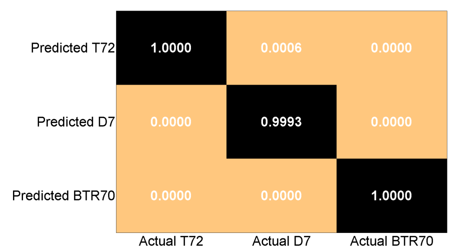

Figure 12. Confusion matrix for 3 target classes using mean=0.5 and variance=0.5. Combined magnitude and phase is used

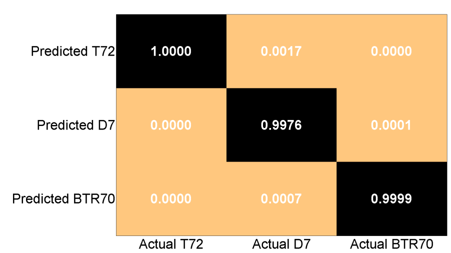

Figure 13. Confusion matrix for 3 target classes using mean=0.75 and variance=0.5. Combined magnitude and phase is used

4. Summary

In this paper we addressed the problem associated with the classification of signatures of objects obtained by coherent sensors whereby the signatures are complex valued. Individual phase and amplitude component of signatures were optimally fused, and their invariant attributes were extracted. These attributes were used to train a sparsity-based classifier. The results of application of this approach were then compared with the corresponding results for the amplitude-only signatures, derived from public-domain MSTAR data of several land vehicles. The performance improvement is shown to be significant when both phase and amplitudes are being used.

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